2020-11-05

Searching for individual determinants of probabilistic cueing in large-scale immersive virtual environments

Baxter, Rory

http://hdl.handle.net/10026.1/16446

10.1177/1747021820969148
Quarterly Journal of Experimental Psychology
SAGE Publications

SEARCHING FOR INDIVIDUAL DETERMINANTS OF PROBABILISTIC CUEING IN LARGE-SCALE IMMERSIVE VIRTUAL ENVIRONMENTS

Rory Baxter

Alastair D. Smith

School of Psychology, University of Plymouth, UK

Correspondence should be addressed to:

Rory Baxter

School of Psychology

University of Plymouth

Drake Circus

Plymouth PL4 8AA, UK

Email: rory.baxter@plymouth.ac.uk

Tel: +44 1752 584800

ABSTRACT

Large scale search behaviour is an everyday occurrence, yet its underlying mechanisms are not commonly examined within experimental psychology. Key to efficient search behaviour is the sensitivity to environmental cues that might guide exploration, such as a target appearing with greater regularity in one region than another. Spatial cueing by probability has been examined in visual search paradigms, but the few studies that have addressed its contribution to large-scale search and foraging present contrasting accounts of the conditions under which a cueing effect can be reliably observed. In the present study, participants physically searched a virtual arena by inspecting identical locations until they found the target. The target was always present, although its location was probabilistically defined so that it appeared in the cued hemispace on 80% of trials. In Experiment 1, when participants' starting positions were stable, a probabilistic cueing effect was observed, with a strong bias towards searching the cued side. In Experiment 2, the starting position changed across the experiment, such that the cued region was defined in allocentric co-ordinates only. In this case, a probabilistic cueing effect was not observed across the sample. Analysis of individual differences in Experiment 2 suggests, however, that some participants may have learned the contingency underpinning the target's location, although these differences were unrelated to other tests of visuospatial ability. These results suggest that the ability to learn the likelihood of an item's fixed location when starting from different perspectives is driven by individual differences in other cognitive or perceptual factors.

INTRODUCTION

Everyday life routinely entails search for a variety of objects in our environment, be it an unplanned hunt for car keys in the home, or a more leisurely pursuit of groceries in a supermarket. Across the great majority of these contexts, search will be not be a novel experience, but instead informed by prior knowledge about the spatial distributions of our quarries. For example, should we be looking for a pack of frozen peas in a supermarket, we would be best placed to begin our search in the freezer section, rather than hunting around in the fresh fruit and vegetables aisle. This type of learning in search behaviour is commonly observed in both human and non-human animal foraging (Maya, Rosetti, Pacheco-Cobos, & Hudson, 2019), since natural resources tend to be distributed probabilistically through space (i.e. some regions are more likely to yield resources than others). Therefore, in order to search efficiently, one needs to attend to regions in which the target is likely to appear, and prioritise exploratory activities to those higher probability regions.

Exploitation of probabilistic cues in human search behaviour has been formally described in the anthropological literature, and the patch choice model (Charnov, 1976; Kelly, 1995) explains predictions in subsistence foraging activities on the basis of previous search experience and the perceived likelihood of future successes. However, formal empirical examination of the psychological processes supporting search decisions of this type have primarily taken a much more Spartan tack by employing the visual search paradigm. In the canonical version of a visual search task, participants are required to report the presence or the absence of a visually-defined target object that is located amongst an array of distractor items, on a 2D monitor screen. Experiments examining the role of learning in search have shown that participants are indeed sensitive to the spatial statistics of an array, and can bias their search to cued regions of space. In the case of contextual cueing, a particular configuration of an array might be repeated over the course of the experiment, with each repetition further associating the target with a specific location (Chun & Jiang, 1998; Brady & Chun, 2007). Search behaviour reveals that participants become more efficient at locating the target object within these contexts, compared to trials in which the target is not located in the cued region of space (i.e. uncued trials), although they report no explicit awareness of the repeated search arrays or any associated search strategy. Similar manipulations reveal that participants can also learn where a target is likely to appear on the basis of a statistical contingency (Geng & Behrmann, 2002; 2005). This probabilistic cueing effect is observed when a participant is presented with a series of randomised arrays, in which the target object is located more often in a certain region of space (e.g. a hemifield, or a quadrant) than another. Over time, participants begin to bias their search towards the cued region, becoming more efficient at locating the target when it appears in the cued region of space and, concomitantly, slower at locating targets in the uncued region. Once again, participants in such experiments do not report any explicit awareness of the contingency, or an associated search strategy, when asked subsequent probe questions, which has led theorists to propose a low-level collicular basis to the effect (Geng & Behrmann, 2002).

Although visual search is considered a controlled context within which scientists can understand domain-general properties of search (e.g. inhibition of return as a 'foraging facilitator': Klein & MacInnes, 1999), the paradigms described above present qualitatively different demands to those experienced in our everyday search of larger environments (Gilchrist, North, & Hood, 2001; Smith, Hood, & Gilchrist, 2008). Since participants in a visual search task are commonly sat in front of a 2D screen, the search array is typically viewed from only one perspective, and usually in the vertical plane. In contrast, search of a large scale environment requires physical movement around the space, perhaps because the target cannot be directly perceived from the present viewing position, or because it requires physical apprehension. This means that we are likely to view the search environment from multiple perspectives and may, therefore, be required to integrate these egocentric (viewer-centred) representations of search space with a more stable and enduring allocentric (array-centred) reference frame. Moreover, previous studies have shown that having participants move around a stable search array can attenuate an individual's ability to learn about statistical contingencies in search tasks (Chua & Chun, 2003; Jiang & Swallow, 2013; Jiang, Swallow, & Capistrano, 2013; Jiang & Won, 2015). Indeed, when these two types of search have been directly compared, results show that the nature of the task demands (i.e. either visual or physical apprehension of the target) elicit differing sets of results (Smith et al. 2008).

As a result of these qualitative differences, it is arguable that a comprehensive assay of human search behaviour must incorporate studies that have explicitly examined performance in large-scale environments. This is not simply a matter of specifying tasks that are somehow closer to naturalistic foraging-like behaviour, but it also carries ramifications for whether the properties of search we characterise are domain-general (i.e. they describe fundamental components of search behaviour that apply in any instance) or whether they are specific to particular tasks, contexts, or response requirements. Experimental studies of large-scale search are not overly abundant, but they include foraging tasks that focus on the acquisition of resources in both real-world environments (Rosetti, Rodriguez, Pacheco-Cobos & Hudson, 2016; Maya et al., 2019), and in immersive Virtual Reality (VR) environments (De Lillo & James, 2012; De Lillo, Kirby, & James, 2014), as well as tasks that have examined the cognitive processes that underpin large scale search. Similarly, these latter studies have also been conducted in both naturalistic real-world environments (Foulsham, Chapman, Nasiopoulos, & Kingstone, 2014) and immersive VR (Ruddle & Lessels, 2006; 2009). Furthermore, explicit examinations of whether visual search phenomena transfer to large scale search have been conducted, specifically looking at contextual cueing (Li, Aivar, Kit, Tong, & Hayhoe, 2016; Li, Aivar, Kit, Tong, & Hayhoe, 2018) and probabilistic cueing (Smith, Hood, & Gilchrist; 2010; Jiang, Won, Swallow, & Mussack, 2014).

As foraging behaviour is reliant on sensitivity to probabilistic cues, examination of statistical learning in large scale environments has primarily focused on how the spatial distribution of target items affects the organisation of search behaviour, and whether different spatial reference frames have a role to play in the representation of this information. In Smith et al. (2010), a series of experiments was conducted to explore, first, whether the probability cueing effects observed in a visual search task by Geng and Behrmann (2002) extend to large-scale search and, second, how cueing relates to certain parameters of the search context. In a novel laboratory, within which lights and switches were embedded into the floor, participants were asked to search an array by activating the switch at each illuminated location (green) until they revealed the target that changed colour (to red) upon activation. The target was always present in the array, and appeared in one hemifield of the array on 80% of trials (the same contingency applied by Geng and Behrmann [2002]). Their data revealed that participants only showed reliable probabilistic cueing effects when they could employ both allocentric and egocentric spatial reference frames in conjunction, and when the arrangement of the search array was stable across the experimental session (i.e. in standard visual search tasks, a new search array is generated on each trial). Under manipulations that isolated the probability cue to allocentric or egocentric spatial reference frames, they observed no probabilistic cueing effects. These data therefore suggest that probability cueing in large-scale search requires a stable environment that allows the searcher to integrate statistical information across both egocentric (viewer-centred) and allocentric (array-centred) reference frames.

Interestingly, however, the findings of Smith et al. (2010) contrast with more real-world data presented by Jiang et al. (2014). In their experiments, they tasked participants with finding a coin on the floor of an outside environment, within a large rectangular space. The rectangular area was split into quarters, with the coin appearing in one quadrant more often than the others. Across three experiments, Jiang et al. (2014) employed experimental manipulations that allowed the coin's location to be learned using a combination of allocentric and egocentric spatial reference frames, or using allocentric or egocentric information alone. Jiang et al. (2014) observed strong probability cueing effects in each of their three experiments – i.e. when participants could only learn the target's likely location using allocentric or egocentric information alone, or when both types of information could be used in conjunction. These data demonstrate a contrasting pattern of results to those observed by Smith et al. (2010), though they may be explained by procedural differences. First, Jiang et al.'s (2014) study took place in an outside environment; an open space rich with visual cues. This contrasts with the laboratory environment Smith et al. (2010) employed, in which incidental environmental cues were purposefully limited by draping a dark curtain around a circular arena (making conditions closer to a simple visual search task). Ruddle and Lessels (2006; 2009) demonstrate that efficient search is facilitated by the richness of an environment, which might explain the discrepancy in results. Additionally, the demands of each task differed: Smith et al.'s (2010) paradigm required participants to physically move throughout the array in order to enact their search (akin to a serial self-terminating visual search task), whereas Jiang et al.'s (2014) task only required participants to indicate that they had identified the location of the target object (i.e. they were not required to physically explore the environment, though the authors state that participants often began the experiment by doing so, before adopting a stationary strategy). The paradigm employed by Jiang et al. (2014) is, therefore, perhaps more similar to a visual search task in terms of its demands, in that participants were not required to move around the space, thus potentially limiting the number of perspectives from which the target could be found. In turn, this may have reduced the processing demands associated with the requirement to learn about the target's statistical distribution, as participants that remained static would not be required to update their position in space.

The conclusions that have been drawn on the basis of performance in these tasks are as much informed by incidences where participants did not appear to learn about the probabilistic cue as those in which reliable cueing effects were observed. So, for example, the fact that Smith et al. (2010) did not find cueing effects for targets specified solely in allocentric or egocentric co-ordinates led them to conclude that neither form of information was itself sufficient to support cueing without being combined with another form of information. In turn, Jiang et al. (2014) argued that their observation of cueing effects within separate reference frames was indicative of greater flexibility afforded by a real-world large-scale search environment. It is, however, important to recognise that the absence of cueing effects at a group level does not necessarily reflect a complete absence of learning across all of the participants tested. So, for example, although the test of allocentric probability cueing in Experiment 3 of Smith et al. (2010) revealed no overall probability cueing effect, there were some small effects of learning, along with evidence for the application of erroneous alternative search strategies. This is, perhaps, indicative of variability in performance that might be reflective of individual differences. Individual differences in large scale search have been observed in atypical populations, such as participants with Autism Spectrum Conditions (Pellicano et al., 2011) and Williams syndrome (Smith, Gilchrist, Hood, Tassabehji, & Karmiloff-Smith, 2009). Accordingly, there may be differences within typical participants that are associated with sensitivity to probability cues. It is certainly the case that there is significant individual variation in more general navigational abilities (for reviews, see: Newcombe, 2018; Wolbers & Hegarty, 2010), and so it stands to reason that associated differences may underlie sensitivity to other environmental cues.

The present report details two large-scale search experiments that were conducted in immersive Virtual Reality (VR) in order to achieve two core aims. The first was to assess whether findings from Smith et al.'s (2010) study could be replicated in a different search context. In particular, Experiments 2 and 3 from that study were recapitulated, since the former (Experiment 2) established a probabilistic cueing effect in large scale search, whereas the latter (Experiment 3) found that the effect was not observed when the cue was specified in an allocentric reference frame only. Since Jiang et al. (2014) found that cueing was observed when it was specified in allocentric coordinates, the present investigation allowed us to examine whether these contrasting effects were due to the information present within the search environment. Immersive VR has been employed previously in studies examining search behaviour and foraging in large scale environments (Ruddle & Lessels, 2006; 2009; De Lillo & James, 2012; De Lillo et al., 2015; Li et al. 2016; 2018), though it has not previously been used to examine probabilistic cueing. In the experiments reported here, a wireless immersive head mounted display (HMD) was utilised, affording full and free motility within a Virtual Environment (VE), without the potential localising cue provided by a cable. More importantly, use of an immersive VE allows total control over an experimental environment, to an extent that is impossible in tasks conducted in the real world, so the visual information available to participants is limited to that visible within the VE. For example, in the experiments reported here, the environment was hidden between trials, ensuring that participants only had access to cues in the environment during trials. This is simpler and more controlled than blindfolding a participant, and maintains a level of experimental control that has perhaps been lacking in previous assays of large-scale cueing behaviour.

The replication of previous experiments in a VR setting also permits an opportunity to address a perceivable weakness in the field of Psychology as a whole, that being whether previously published experimental findings are indeed replicable (Pashler & Wagenmakers, 2012). This is especially pertinent in the present enquiry, given the discrepancy between the findings of Smith et al. (2010) and Jiang et al. (2014) as to whether probabilistic cueing is evident in allocentric spatial reference frames. Furthermore, the increasing adoption of Bayesian analytical techniques, allows us to examine the strength of the evidence which, when examining a phenomenon that may result in a null result, allows for a quantification of evidence for an absence of a difference between experimental conditions (Dienes, 2014).

The second core aim of the present study was to take additional measures of individual difference in order to ascertain whether participant performance in other visuospatial domains might predict sensitivity to probability cues (i.e. the likelihood that a spatial cue is learnt). Alongside the search task, participants also completed the Vandenberg and Kuse (1978) Mental Rotation task (MRT; adapted by Peters et al., 1995) and the Kozhevnikov and Hegarty (2001) Perspective Taking task. The MRT is a measure of mental object rotation, in which participants are presented with a series of geometric shapes, rotated along their axes, and are required to identify which of the shapes are the same. The Perspective Taking task is a measure of the ability to shift one’s imagined perspective to another location. participants are presented with a top down array of objects, and required to imagine themselves at the location of one whilst facing another – their task is then to indicate the egocentric direction of a third object, from their imagined point of view. Both tasks were administered as they have previously been found to predict large scale spatial abilities such as navigation (Kozhevnikov, Motes, Rasch, & Blajenkova, 2006; Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013). Furthermore, the nature of allocentric manipulation in this study’s Experiment 2, might require participants to engage in a mental transformation of the space, as the cued region of space would be fixed, but their starting position and heading would change from trial to trial. In addition, participants completed the Santa Barbara Sense of Direction Scale (SBSOD; Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002), a self-report measure of navigational ability, to identify if there was a link between large scale search efficiency and more general large scale spatial abilities such as navigation. Participants also completed the amended Edinburgh Handedness Inventory (Oldfield, 1971; Schachter, 2000), as laterality has previously been associated with search efficiency (Smith, Gilchrist, & Hood, 2005) although not necessarily in the case of probability cueing (Smith et al., 2010).

GENERAL METHOD

Both experiments reported here were conducted in immersive VR and followed the same basic structure, adapted for this novel context from that of Smith et al. (2010). The methodology and manipulations unique to each experiment are described separately and respectively.

Apparatus

Each experiment took place in the University of Plymouth's large scale immersive VR laboratory. This facility features a relatively large (5.4m x 6.5m) clear workspace, dedicated to large-scale motile paradigms. The VE was displayed to participants via an HTC Vive Pro VR HMD with an HTC Vive Wireless Adaptor. Participants interacted with the environment using a single HTC Vive Pro controller and their body positions were tracked using a Vive tracker, which was mounted on a belt and worn around the participants' midriff. A researcher was present in the room throughout each experimental session, and could observe the participant's current view in the HMD through a concurrent display on the desktop PC that was running the experimental task. The HMD was equipped with integrated headphones, to attenuate noise external to the experimental task.

The task and VEs were built using Unity Professional Software (Version 2019.2.12; Unity Software, 2019), and run through the Unity Professional editor, using the SteamVR plugin (Valve Software, 2019). The VE for the experimental trials comprised a circular arena with a diameter of 4.5 metres. The textures used in the experiment were photorealistic seamless textures, selected to minimise the presence of additional landmarks cues in the environment. The search array comprised 16 columns, each 1 metre tall with a diameter of 20 centimetres. These were textured with a seamless photorealistic texture, colourised within the Unity software to be red (RGB: 158-0-0). The target column, when found by a participant changed colour from red to turquoise (RGB: 43-124-255).

The search array used in the experimental trials was randomly generated for each participant, under specified constraints. Columns were generated in 16 out of 46 possible locations, organised in concentric octagons with the mid-sagittal column of potential locations removed (this was so that no potential locations were positioned directly on the midline of the search space, from the perspective of the starting positions; see Figure 1). The array was centred within the circular arena, and its entirety fit within a 3x3m region. The mid-sagittal axis was used to divide the locations into cued and uncued hemispaces. Half of the columns would be placed at randomly selected locations in the cued region and the remaining 8 columns would be placed at randomly selected locations in the uncued region (see figure 2A for an example of an array, and 2B for a participant's in-trial perspective of that same array). This randomised distribution of the columns across each side of the array ensured that each region's layout was distinct for each participant, across both experiments.

Participants' starting position in Experiment 1 was located 2.1 metres from the centre of the space, along the mid-sagittal axis, and was indicated by a green disc with a diameter of 50 centimetres. The two starting positions in Experiment 2 also indicated by discs and were both 2.1 metres either side of the central point of the arena along the midline. The two starting position markers in Experiment 2 could be either green or orange, with the green starting position indicating the starting position to be used for the subsequent trial.

Design

As described previously, the search array was randomly generated and formed of two hemispaces, comprising 8 columns each. Following the contingency employed by Smith et al. (2010) and Geng & Behrmann (2002; 2005), the target column was located in the cued side of the array on 80% of trials, and in the uncued side on the remaining 20% of trials. The identity of the cued and uncued regions were counterbalanced across participants – i.e. 50% of participants were cued to one allocentrically-defined region, irrespective of their starting position, and 50% were cued to the other. During the search task, participants were required to search the array for the target column: specifically, the column that changed colour when activated. There was always a target column present in each trial, and its identity was randomised under the constraints that there would be 4 trials in which the target was located in the cued region of space (cued trials) and 1 trial in which the target was located in the uncued region of space (uncued trial) out of every 5 trials. The identity was further constrained, with each column on the cued side being the target once every 8 cued trials. A similar constraint was applied to the uncued trial targets, with each uncued column being a target every 40 trials. This reduced the probability of a column being selected as the target for two consecutive trials, to attenuate potential repetition priming effects (Walthew & Gilchrist, 2006).

Participants completed 80 trials, 64 of those being cued and the remaining 16 being uncued. The trials were split into two blocks of 40 trials which, in Experiment 1, were either side of a break of up to 5 minutes. As only one participant elected to take a short break in Experiment 1, the option was removed for Experiment 2.

Procedure

At the start of the experimental session, participants completed the SBSOD (Hegarty et al., 2002), the amended Edinburgh Handedness Inventory (Oldfield, 1971; Schachter, 2000), and the VR Sickness (Kim, Park, Choi, & Choe, 2018) questionnaires. Participants then completed the Perspective Taking task (Kozhevnikov & Hegarty, 2001) and the MRT (Vandenberg & Kuse, 1978; Peters, 1995). The MRT was administered over two halves, with participants completing the each group of 12 trials within a 3 minute time limit, with a 3 minute break between both halves.

Once the questionnaires and cognitive measures were completed, participants were then equipped with the VR system. Before starting the experimental task they were shown the Steam VR Chaperone system. This is a safety feature designed to prevent participants walking into the physical walls of the laboratory. The Chaperone system comprises a green mesh which would only appear when a piece of the HTC Vive equipment entered within 50cm of a safe 5.4m x 6.5m space within the laboratory. Participants were instructed that the green mesh was the location of the laboratory walls and that it was, therefore, advisable not to walk any further. This was sufficient to ensure that no participants experienced any contact with the walls of the laboratory, but also meant that they were confident to move freely around the search space without fear of unexpected collision.

Participants initially completed four practice trials, which took place in a simplistic environment comprising a single plane and a search array comprising 5 columns identical to those used in the experimental trials. These columns were located at the centre of the environment and arranged in the formation that one would see on dice (i.e. four columns forming vertices of a square, with the final column positioned in the centre; see figure 2C). In each practice trial, the target column was one of the four corner columns, each designated in a random order.

Participants' starting positions for each trial (both practice and experimental) were initially indicated with the environment hidden from view – i.e. the entire visual scene was black, and the only visible object was the marker for the starting position. Participants were required to stand over this marker and to press the trigger on the controller to initiate the trial. The trial would only initiate when the tracker, worn around each participant's midriff, was positioned over the starting position marker. When stood over the starting position marker, participants intuitively faced towards the centre of the arena to begin each trial. Once the trial had been initiated the experimental environment was revealed to participants and the starting position marker was hidden. Participants would be required to inspect the columns in the search array to find the target. An inspection involved placing the controller inside of a column and pressing the trigger. To compensate for the relative difference in tactile feedback, compared to the mechanical activation of individual switches in Smith et al.'s (2010) study, each inspection was accompanied by audio feedback (a buzzer sound) to make participants aware that their action had been registered by the program. When the target column had been inspected, it changed colour and participants received alternative audio feedback (a chime) indicating that the target had been found. The trial environment remained visible with the target column still highlighted in turquoise for 5 seconds, after which the environment, including the search array, was hidden from view (the entire environment faded to black), and the starting position marker for the next trial was then made visible to participants.

At the end of the experiment, participants were asked about their awareness of the probabilistic manipulation. This assessment comprised three probe questions, with the first asking participants if they used a specific strategy to find the target on each trial. If participants did not respond by explicitly stating that they focused their search on the cued regions, they were then asked if they had a sense as to where the target was likely to appear on a given trial. If they did not answer this question with an indication that they thought the target was likely to appear in the cued region, they were asked a final question: “If I told you that the target was more likely to be in one side, would you be able to guess which one?” These measures have been previously used to assess the level of explicit awareness of probabilistic manipulations (Chun & Jiang, 1998; Smith et al., 2010), and provide insight into the extent of a participant’s awareness (i.e. a correct answer after the first question demonstrates clearer knowledge of the manipulation than a correct answer to a binary left/right alternate forced choice). After the probe questionnaires had been answered, participants then completed the VR Sickness questionnaire (Kim et al., 2018) again.

Analysis

Four main dependent variables were analysed in the two experiments here reported. The first was the latency between the trial beginning and the target being found, recorded to millisecond accuracy. Second was the total number of individual inspections to search locations (i.e. activation of columns) made in a single trial. Third was the length of the search path taken by the participant, in Unity metres (analogous to real world metres). This was computed from the distance between the starting position and the first column inspected, then the distance between all subsequent columns inspected. The final measure was the percentage of trials in which a column in the cued region of space was visited first. Search latency, path length, and the number of searches made were each analysed using a 2 (probability: cued, uncued) x 2 (block: Block 1, Block 2) repeated measures ANOVA. To ensure the

ANOVA assumption of normality was not violated, latency data was transformed using Tukey's Ladder of Power transformations for both experiments. First choice data in each block was analysed using a one sample t-test, compared against a chance level of .5 (i.e. an equal proportion of first visits to each side). First choice data was also compared using a paired samples t-test, to compare the proportion of trials which started with an inspection in the cued region across trial blocks. As this might not be the only driver of a participant's first choice of column to inspect, t tests were also conducted on the proportion of trials in which the first inspected column was located in the region that included the closest column to the starting position, an indicator of a systematic approach to first inspection choice. As the array layouts were randomised, for some participants, there were two regions in which the closest columns were equally proximal. In these instances, these trials were removed from the analyses. Additionally, similar analysis was conducted on the proportion of trials in which the region to the left of the participant's starting location was inspected first, which would be indicative of a left side bias (Sosa, Teder-Sälejärvi, & McCourt, 2010). These two supplementary analyses were compared to a chance level of .5.

The measures above, along with those recorded from the SBSOD and Edinburgh Handedness Inventory questionnaires, and the perspective taking task and MRT were analysed using a Pearson's correlation, to identify associations between these variables. As efficient searching in this task involves focusing search in the cued region of space, difference values were calculated for search latency, path length and the number of searches made in a trial. These values comprised the difference between each participant's mean value on cued and uncued trials for each measure. A larger value would indicate a participant who was more efficient at learning the probabilistic distribution, as it indicates a focus on the cued region of space. These difference measures, alongside the first choice measures, may provide insight into individual differences in search strategy (i.e. do individuals follow a systematic search pattern, or do they prioritise their search in a particular region of space?). Additionally, the number of revisits to each previously inspected column were recorded for each participant, and entered in to the correlation matrix, as this provides a further measure of search efficiency (i.e. more efficient search involves fewer revisits to previously inspected columns). For the correlation analysis, participants' probe question answers were coded depending on which question, if any, they correctly identified the cued region. If they identified it correctly in the first question, their probe question score was coded as 3, if they identified it in the second question, their score was coded as 2, and if they identified it in the final question, their score was 1. If they did not identify the cued region correctly in the final forced-choice component, their score was coded as 0.

Participants' Laterality Quotient, as measured by the Edinburgh Handedness Inventory, was coded such that lower scores indicated left laterality, and higher scores indicated right laterality. The SBSOD was coded with higher scores indicating greater navigational proficiency, and lower scores indicating lower proficiency. For the VR Sickness Questionnaire, lower scores were coded as a lower severity of side effects, and higher scores coded as indicating more severe side effects.

As Experiment 2 involved the examination of a manipulation that had not previously yielded significant behavioural effects (i.e. Experiment 3 from Smith et al., 2010), Bayes Factors were computed for the analyses detailed previously, and were interpreted as per Jeffreys (1961). Bayes Factors for the ANOVAs and t-tests were computed in R 3.63 (R Core Team, 2020), using the BayesFactor package (Morey & Rouder, 2018), and employed uninformed priors. Bayes Factors for the correlations and binomial tests were computed using JASP (JASP Team, 2019). These analytical techniques allow for a greater insight than traditional null hypothesis significance testing, since they provide quantification of evidence for the presence, or absence, of a difference between conditions.

EXPERIMENT 1

This Experiment was designed to investigate whether the basic large-scale probability cueing effect reported by Smith et al. (2010; Experiment 2), could be replicated in immersive VR. Participants searched for a target column within a fixed search array – i.e. the locations to be searched remained stable across trials, rather than being arranged differently on each trial (as is usually the case in a standard visual search paradigm). The target appeared in one half of the array on 80% of trials (cued) and in the other half on the remaining 20% of trials (uncued). As the starting position was in the same location for the duration of the experiment, the cued side was specified in both allocentric (array-centred) and egocentric (from the perspective of the participant, at the beginning of each trial) reference frames. The cued region could therefore be identified in relation to the layout of the array (allocentric response), or on the basis of an initial directional response at the start of each trial (egocentric response).

Method

Participants. Participants were recruited from the University of Plymouth (*N* = 24; 19 female), and were given course credit in return for participation. The age of participants ranged from 18 to 28 years (mean = 20.33, *SD* = 2.32). Each participant was physically able to explore the immersive VR space, and did not experience any side effects from the use of the HMD (see Experiment 1 Results).

Design. This experiment's design follows the procedure detailed in the General Method section, with participants beginning each trial from a fixed starting point.

Results

Descriptive statistics for trial latencies, path length, the number of column inspections, and percentage of trials with a first choice in the cued region are visualised in Figure 3. For latency to find the target, there was a significant effect of probability, $F_{(1, 23)} = 8.96$, $p = .006$, $\eta_p^2 = .27$, $BF_{10} = 66.48$, and block, $F_{(1, 23)} = 34.54$, $p < .001$, $\eta_p^2 = .6$, $BF_{10} = 255.87$, with search latencies being shorter in cued trials than uncued trials, and shorter in Block 2 compared to Block 1. There was no interaction effect between the two variables, $F_{(1, 23)} = 0.34$, $p = .57$, $\eta_p^2 = .01$, $BF_{10} = 0.29$, with the Bayes Factor suggesting an absence of an interaction.

There was a significant effect of probability on measures of both path length, $F_{(1, 23)} = 12.17$, $p = .002$, $\eta_p^2 = .18$, $BF_{10} = 7340.34$, and the total number of inspections made $F_{(1, 23)} = 11.11$, $p = .003$, $\eta_p^2 = .33$, $BF_{10} = 35293.47$. This revealed shorter search paths and fewer inspections for cued trials, compared to uncued trials. In contrast, for path length, there was no significant effect of block, $F_{(1, 23)} = 3.4$, $p = .08$, $\eta_p^2 = .13$, $BF_{10} = 0.37$, and no significant interaction between the factors $F_{(1, 23)} = 0.02$, $p = .88$, $\eta_p^2 = .001$, $BF_{10} = 0.28$, with the Bayes Factor suggesting an absence of an interaction. Similarly, for the number of inspections, there was also no significant effect of block $F_{(1, 23)} = 2.47$, $p = .13$, $\eta_p^2 = .1$, $BF_{10} = 0.34$, and no significant interaction between the factors $F_{(1, 23)} = 0.03$, $p = .87$, $\eta_p^2 = .001$, $BF_{10} = 0.31$, with the Bayes Factor again suggesting an absence of an interaction.

The percentage of trials that started with an inspection in the cued region of space did not differ to a chance level of .5 in trial Block 1, $t_{(23)} = 1.58$, $p = .13$, $BF_{10} = 0.64$ or in trial Block 2, $t_{(23)} = 1.68$, $p = .11$, $BF_{10} = 0.73$. Furthermore, there was evidence to suggest that there was no difference between the number of trials that began with an inspection of the cued region in trial Block 1 and in trial Block 2, $t_{(23)} = 0.97$, $p = .34$, $BF_{10} = 0.33$. To identify alternative antecedents of participants' first choice of column to inspect, a second t-test was performed that compared the percentage of searches that started with an inspection of a column in the region closest to the starting position (i.e. the side of the array featuring the closest column to the starting position, regardless of the side that it occupied) to chance (*M* = 67.2%, *SE* = 6.4%). Five participants were removed from this analysis as there were two columns equally close to the starting position in the randomly generated arrays on each trial). This showed a significant difference to a criterion of .5, $t_{(18)} = 2.7$, $p = .015$, $BF_{10} = 3.79$. Finally, to investigate whether a participant's first choice was driven by a left side bias (Sosa, et al., 2010), a final t-test was conducted on the percentage of trials starting with a search in the left side of the array (irrespective of the side of the probability cue). The mean percentage of trials started with an inspection in the left side of the array was 52.3%, with *SE* of 1.3%. There was no significant difference from a chance value of .5, though there was no evidence of an absence of a difference, $t_{(23)} = 0.36$, $p = .72$, $BF_{10} = 0.23$.

In total, 83.33% of participants correctly identified the cued region in their responses to the awareness probes: 12.5% identified the cued region in the first question (score: 3), 20.833% identified the cued region in the second question (score: 2), and 50% identified the cued region in the third and final question (score: 1). To provide a basic assay of participants' awareness of the manipulation, a binomial test was conducted on the probe question data. For the purposes of this test, participants were coded as being aware of the manipulation if they responded with the correct identity of the cued region in any of the three questions (i.e. they had a score of 1 or above). The results showed that the number of participants that correctly identified the cued region (at any stage of the probe procedure) was significantly greater than chance (i.e. 50% of participants), $p < .001$, and there was decisive evidence to support this, $BF_{10} = 126.253$.

Difference measures between cued and uncued trials were calculated for trial latency, path length, and the number of inspections in a trial. These, alongside the participant's level of awareness (measured by the probe questions), the percentage of trials in which the cued region was inspected first, and the percentage of trials in which the closest column was inspected first, were entered into a correlation matrix alongside the SBSOD and Edinburgh Handedness Inventory questionnaires, and the data from the MRT and Perspective Taking Task (see Table 1). There were significant correlations between each of the difference measures: trial latency and path length, R^2 = .92, p < .001, BF_{10} = 3.723e+7; trial latency and number of columns inspected, R^2 = .92, p < .001 BF_{10} = 6.028e+7; and, path length and the number of columns inspected, R^2 = .99, p < .001, BF_{10} = 2.055e+133, with each correlation supported by decisive evidence from the Bayes Factor. This suggests that they reliably measured the same aspects of search performance. There was also a significant correlation between the Edinburgh Handedness Laterality Quotient (LQ) and a participant's SBSOD score, R^2 = .51, p = .011, BF_{10} = 5.934, which suggests there is strong evidence that, in this sample, participants who were more strongly lateralised to the left, self-reported as better navigators. Furthermore, there was also a significant negative correlation, albeit with inconclusive Bayesian support, between LQ and the proportions of trials which started with an inspection in the closest region of the array, R^2 = -.47, p = .044, BF_{10} = 1.872. This indicates that the more left lateralised a participant was, the more likely they would be to inspect a column in the closest side of the array first.

It is interesting to note that there was no significant correlation between the proportion of trials starting with a search in the cued region and the difference measures for: trial latency, R^2 = .29, p = .16, BF_{10} = 0.632; searches made, R^2 = .22, p = .31, BF_{10} = 0.411; and, path length, R^2 = .22, p = .30, BF_{10} = 0.418. Furthermore, there were also no significant correlations between probe awareness and the difference measures for: trial latency, R^2 =0.26, p = .23, BF_{10} = 0.5; searches made, R^2 = .18, p = .39, BF_{10} = 0.358;

and, path length, R^2 = .18, p = .39, BF_{10} = 0.359. This suggests that the extent of a participant's explicit awareness of the statistical contingency was not necessarily related to their search efficiency, and that sensitivity to the probabilistic cue may not have guided a participant's initial choice of inspection location.

To identify whether participants suffered any negative effects from using the VR equipment, a t-test was conducted on the pre- (M = 2.85) and post- experiment (M = 1.88) VR Sickness questionnaire scores. This test was found no significant difference between the two measures, t = 1.54, p = .137, BF_{10} = 0.61, suggesting that sensations of nausea did not differ between pre- and post-experiment measures, though there was only anecdotal evidence from the Bayes Factor to suggest an absence of this difference.

Discussion

In Experiment 1 we observed a replication of a probability cueing effect in immersive VR that has previously been reported in large-scale real-world search (Smith et al., 2010; Experiment 2). Participants were faster to find the target in trials when it was located in the cued side of space and, therefore, slower to activate it when it appeared in the uncued side. This is indicative of a search bias towards the cued (or "rich") side of space and was also reflected in other dependent measures – i.e. participants also took a shorter path to find the target, and made fewer inspections, when it was in the cued region. Furthermore, many participants (83.33%) correctly identified that the target was more likely to appear in the cued region of space when their awareness of the manipulation was probed.

There were, however, two general findings that were not consistent with those of Smith et al. (2010) in their Experiment 2. First, there was evidence that participants were no more likely to begin their search in the rich region of space than in the sparse region of space. This is likely due to procedural differences as, in the present experiment, there was often no cost to inspecting the closest column due to its potential proximity to the starting location. Indeed, this interpretation is supported by the observation that participants inspected the side of the array that contained the closest column more often than chance. This contrasts with Smith et al.'s (2010) search array, in which both the cued and uncued region were more distal from the starting position, thus associating greater cost with the first inspection. The second difference was that the present experiment showed evidence for an absence of interaction effects (between trial type and experimental block) for the behavioural measures of search efficiency. This indicates that the cueing effect was likely established early on, and that its strength was maintained across the course of the experiment. This differs from the results from Smith et al.'s (2010) Experiment 2, in which a cueing effect was observed within the first half of the experiment, and was further strengthened across the course of the experiment.

A further procedural difference between this experiment and Smith et al.'s (2010) Experiment 2 is that the test environment was not continuously visible during the course of the experiment, with the array and environmental setting being hidden from view between trials. One might expect this to have impacted upon the probabilistic cueing effect, especially given the narrative of Smith et al.'s (2010) six experiments. However, as we have seen, only slight discrepancies between experimental findings are apparent – i.e. the absence of a cueing effect in first-visit behaviour, and the lack of interaction effects between trial type and block. This is perhaps further evidence for the integral role of the array's perceptual stability to probabilistic cueing in large scale space – i.e. in the studies reported by Smith et al. (2010), and Jiang et al. (2014), the search tasks were conducted in real physical spaces, where the environment could not be hidden from participants (although Jiang et al. employed a blindfold when setting-up individual trials). In contrast, the current paradigm allowed for the environment to be extinguished between search trials, which may have increased task difficulty for some participants if they required themselves to be reoriented in the test space at the start of each trial (i.e. as a result of the unstable percept of the array). Finally, the observed probabilistic cueing effect further confirms that it can be robust to movement around a large scale space (see also: Jiang et al., 2014). This contrasts with visual search evidence for a deleterious effect of egocentric movement on some forms of statistical learning (e.g. in the case of contextual cueing: Jiang et al., 2013).

One surprising element of the results is the apparent absence of a relationship between some of the performance measures. The lack of reliable correlation between the awareness probe and behavioural measures of search efficiency is surprising, since one would expect an explicit awareness of where the target is likely to be in space to drive the focus of a participant's search. This may be a result of the awareness measure not being sufficiently sensitive to pick up on participants' performance over the course of the experiment (Vadillo, Linssen, Orgaz, Parson, & Shanks, 2019). Furthermore, if a participant appeared to be searching efficiently, then it would be expected that they would focus their initial search in that region, and yet first inspection choice was not correlated with measures of search efficiency. This further supports the idea that first choice was, instead, seemingly driven by the proximity of locations to the starting position.

It is worth noting that, contrary to predictions, there was no reliable relationship between additional measures of spatial ability (i.e. mental image manipulation, sense of direction) and performance in the large-scale search task. This might perhaps be due to the combination of cues available to participants in this first experiment – i.e. the identity of the cued region could be learned using contributions from both allocentric and egocentric spatial reference frames (i.e. it was fixed with respect to both), which has previously been found to produce strong cueing effects (Smith et al., 2010). As such, we predicted that the manipulation of spatial reference frames in Experiment 2 might also reveal stronger evidence for individual differences in performance.

EXPERIMENT 2

This second Experiment followed the design of Smith et al.'s (2010) Experiment 3, and was conducted to investigate whether the probabilistic cueing effect could be observed when the cue was specified in an allocentric reference frame only and, therefore, decoupled from the participant's starting position. This manipulation was achieved by specifying two starting positions, either side of the centre of the arena. This meant that a change in starting position would be associated with a change in egocentric perspective at the beginning of the trial, but the cued region of space would occupy a fixed allocentrically-defined region within the virtual environment. Whilst there were no distinguishing landmarks within the circular arena, there were a number of cues that could contribute to participants successfully updating their location in the environment and building a statistical association between the target and the environment. First, the two different starting positions consistently occupied the same location in space, meaning that path integration (and similar idiothetic mechanisms based on movement through space) should contribute to a coherent and consistent sense of beginning each search from one of two particular places. Furthermore, each hemifield of the space contained its own distinct configuration of search locations, providing stable information about the display, and a core cue to distinguish one side from the other.

Method

Participants. Participants were recruited from the University of Plymouth (*N* = 23; 21 female), and were given course credit in return for participation. The age of participants ranged from 19 to 34 years (mean = 21.57, *SD* = 3.58). Each participant was physically able to explore the immersive VR space without experiencing any negative effect from the use of the immersive VR system (see Experiment 2 Results).

Design**.** This experiment mostly follows the general procedure detailed previously in this report. However, in this particular version of the task, participants began each trial from one of two different starting positions. The starting position for each trial was counterbalanced, with 20 trials in each block starting from one end of the midline and 20 trials from the other, with an even split every 10 trials. The order in which the starting positions were selected for each trial was block randomised based on these constraints. Additionally, the target identity and trial type was randomised with counterbalancing constraints. These constraints were devised so that each column would be a target an equal number of times in each trial block. Additionally, the starting position for each trial was counterbalanced so that each starting position would be used in an equal number of trials in each block.

Results

Descriptive statistics for trial latencies, path length, the number of column inspections, and percentage of trials with a first choice in the cued region are visualised in Figure 4. There was a significant effect of block on search latency in this experiment, $F_{(1, 22)} = 36.2$, $p < .001$, $\eta_p^2 = .62$, $BF_{10} = 28.01$, indicating that participants were faster to find the goal in Block 2, compared to Block 1. There was, however, no reliable effect of probability on search latency, $F_{(1, 22)} = 0.09$, $p = .77$, $\eta_p^2 = .004$, $BF_{10} = 0.23$, with the Bayes Factor suggesting there was no difference between cued and uncued trial latencies. Furthermore, there was an absence of an interaction between the two factors, $F_{(1, 22)} = 0.63$, $p = .44$, $\eta_p^2 = .03$, $BF_{10} = 0.33$.

Analysis of path length revealed no significant effects of either probability, *$F_{(1, 22)} = 2.25$, $p = .15$, $\eta_p^2 = .09$*, BF_{10} = 1.36 or block, *$F_{(1, 22)} = 0.19$, $p = .67$, $\eta_p^2 = .008$*, BF_{10} = 0.24, nor was there a significant interaction between factors, *$F_{(1, 22)} = 1.1$, $p = .31$, $\eta_p^2 = .05$*, BF_{10} = 0.42. A similar pattern of results was observed for the number of inspections made, with no significant effects of either probability, *$F_{(1, 22)} = 1.15$, $p = .29$, $\eta_p^2 = .05$*, BF_{10} = 0.68 or block, *$F_{(1, 22)} = 0.09$, $p = .77$, $\eta_p^2 = .004$*, BF_{10} = 0.22, nor was there a significant interaction between factors, *$F_{(1, 23)} = 1.17$, $p = .29$, $\eta_p^2 = .05$*, BF_{10} = 0.9.

Similarly to Experiment 1, participants were no more likely to initially inspect a column in the cued region of space than chance in trial Block 1, $t_{(22)}$ = -0.9, p = .381, BF_{10} = 0.32 or trial Block 2, $t_{(22)}$ = -0.97, p = .35, BF_{10} = 0.33. Again, as in Experiment 1, participants did not start their search more often in the cued region in trial Block 2 than in trial Block 1, $t_{(22)}$ = 0.58, p = .57, BF_{10} = 0.26. Furthermore, for the trials that permitted appropriate analysis (half of nine participants' data were excluded due to one starting position being equally close to both region) , participants did inspect the region which contained the closest column more often than a chance value of .5 (*M* = 55.2%, *SE* = 4.51%), $t_{(22)}$ = 3.59., p = .002, BF_{10} = 22.98. Finally, there was decisive evidence to suggest that participants inspected the left side of the array first, relative to their starting position, less often than chance (*M* = 18.2%, *SE* = 0.53%), $t_{(22)}$ = -12.19., p < .001, BF_{10} = 3.061e+7.

In total, 56.52% of participants correctly identified the cued region at some point in the awareness probe procedure: 17.4% identified the cued region in the first question (score: 3), 13.01% identified the cued region in the second question (score: 2), and 26.09% identified the cued region in the third and final question (score: 1). The binomial test for awareness in Experiment 2 showed that the proportion of participants that correctly identified the cued region of space in one of the probe questions was not significantly greater than chance (i.e. 50% of participants), p > .05, and there was substantial evidence to suggest that there was no difference between the number of participants that did or did not identify the cued region, BF_{10} = 0.306.

A similar correlation matrix to that presented in Experiment 1 was generated to identify relationships between variables (see Table 2). In this experiment, there was a significant negative correlation, albeit with inconclusive Bayesian support, between the proportion of trial starting with an inspection of a column in the closest region first, and the proportion of trials initiated by inspecting a column in the cued region first, R^2 = -.45, p = .031, BF_{10} = 2.31. This indicates that participants started each trial inspecting either the cued region or the region that contained the closest column, irrespective of whether this closest region was cued or uncued. Additionally, the percentage of trials in which the cued region was inspected first correlated with the difference measures for trial latency, R^2 = .46, p = .027, BF_{10} = 2.559, number of columns inspected, R^2 = .49, p = .018, BF_{10} = 3.69, and path length, R^2 = .49, p = .017, BF_{10} = 3.77, though there was only anecdotal evidence from the Bayes Factor to support the correlation with the latency difference measure. This indicates that participants who inspected a column in the cued region first were more likely to search efficiently, as well as the inverse, that participants that did not search in the cued region first were more likely to be inefficient.

There was a significant negative correlation between the number of trials in which the region that contained the closest column was inspected first, and the number of revisits in a trial, R^2 = -.48, p = .019, BF_{10} = 3.42. This suggests that participants who inspected this closest region first may have searched systematically in a travelling salesman approach, thus reducing the likelihood of having to revisit a column. There was also a significant negative correlation between Perspective Taking task error and MRT accuracy, R^2 = -.63, p = .001 BF_{10} = 33.56, which contrasts with the lack of such a correlation in Experiment 1. Similarly to Experiment 1 there were significant correlations between the three difference measures, trial latency and path length, R^2 = .93, p < .001, BF_{10} = 5.912e+7, trial latency and number of columns inspected, R^2 = .94, p < .001, BF_{10} = 1.113e+8, and path length and the number of columns inspected, R^2 = .96, p < .001, BF_{10} = 1.108e+10, again indicating, with decisive evidence from the Bayes Factor analysis, that all three variables are measuring the same aspects of performance.

Similar to Experiment 1, It is interesting to note that there was no significant correlation between probe awareness and the difference measures for: trial latency, R^2 =0.33, p = .12, BF_{10} = 0.8; searches made, R^2 = .39, p = .64, BF_{10} = 1.3; and, path length, R^2 = .37, p = .08, BF_{10} = 1.8. Additionally, there was no significant correlation between probe awareness and the proportion of trials initiated with an inspection in the cued region, R^2 = .03, p = .9, BF_{10} = 0.26. This suggests that the extent of a participant's explicit awareness of the statistical contingency was not related to their search efficiency, and that sensitivity to environmental statistics may not have guided a participant's initial choice of inspection.

Similar to the analysis for Experiment 1, a t-test was conducted on the pre- (M = 3.57) and post-experiment (M = 3.91) VR Sickness questionnaire scores. This test also found no difference between the two scores, t = -0.54, p = .598, BF_{10} = 0.25, suggesting that participants did not suffer adverse effects from using the VR equipment in this experiment.

Discussion

To investigate whether probability cueing could occur in an allocentric reference frame (i.e. biasing search to a particular region of environmental space, regardless of egocentric viewpoint), participants began each trial from one of two starting positions that were located at either end of the array's mid-sagittal axis. The data showed that, on the whole, there was no reliable probabilistic cueing effect across each of the behavioural measures, with search behaviour not seeming to differ between cued and uncued trials, and participants' first inspection likely being driven by the proximity of the search locations to their starting position. These measures of efficiency are supported by the analysis of the probe questions, which presented additional evidence to suggest that participants did not explicitly learn about the manipulation (57% of participants identified the cued region). It may be, however, that the type of awareness probe employed in this experiment was not sensitive enough (Vadillo et al., 2019), which is, as in Experiment 1, indicated by the absence of correlations between the awareness probe questions and measures of search efficiency. A greater understanding of participants' awareness may be elicited through more regular probe trials, following the formats described by Vadillo et al. (2019). These could be introduced in regular trial blocks during the experiment and comprise participants ranking their opinion on how likely the target was to appear in a specific region. This is supported by the awareness probe question not being associated with other measures of search efficiency, in either this Experiment, or Experiment 1, indicating that it may not appropriately capture a participant's awareness of the probabilistic distribution of the target's location.

There may, however, be individual differences in the degree to which participants formed or applied particular search strategies. This is shown by correlation analysis demonstrating that participants who tended to search in the cued region of space first were more efficient at finding the target, with these participants taking shorter paths, inspecting fewer columns on cued trials than on uncued trials, and finding the target faster, though there was only anecdotal evidence to support this last correlation. This is suggestive of a strategy that involved focusing search on the cued region. In contrast, participants that did not show a tendency to inspect a column in the cued region first tended, instead, to preferentially search the closest column, indicated by the negative correlation between these two measures. This is suggestive of an alternative strategy, which involved initiating search with an inspection of the closest column, and systematically inspecting each column in the array using a travelling salesman-type strategy. This would not be an efficient strategy for this task, due to the target's probabilistic distribution. This inefficiency is shown by the absence of a strong correlation between the proportion of trials initiated with an inspection of the closest column and the differences between trial types in latency, path length, and number of inspections. Furthermore, the significant negative correlation between the number of revisits and the number of trials that started with an inspection of the closest column also suggests a systematic approach, since a strict travelling salesman strategy (i.e. inspecting the next closest location) should be more likely to preclude revisits to previously inspected locations.

This potential difference in strategy selection may reflect individual differences in the ability for participants to orient at the start of each trial within the virtual environment. Since the environment was extinguished between trials, it is possible that participants may not have been able to develop a stable allocentric representation of the cued regions' location. If one was disoriented in this environment, then the most effective strategy would be to select the closest column and then systematically inspect the subsequent closest columns. There is, however, evidence that even children can generate an allocentric representation of navigated space when blindfolded (Bostelman, Lavenex, & Banta Lavenex, 2020), which would suggest that participants in this experiment should have been able to reliably orient in the test environment, and maintain an enduring representation of their place within it, even when it was hidden from view.

These findings replicate those of Smith et al.'s (2010) Experiment 3, with an absence of a group-level probabilistic cueing effect for a cue specified within an allocentric reference frame. This indicates that Smith et al.'s (2010) findings were not necessarily a product of a specific procedure, and suggests that the immersive VR iteration of the task provides a reliable replication. A core difference between this Experiment and the equivalent reported by Smith et al. (2010) is in the physical costs associated with making an inspection – i.e. whereas participants in VR made an inspection by pressing a trigger at waist height, Smith et al.'s apparatus required them to bend down and activate switches that were embedded in the floor. One might predict that such differences would have a large effect on search behaviour (for discussion on search costs and memory see: Gilchrist et al., 2001), and yet the present results suggest that the reduced energy demands did not seem to moderate behaviour in response to a probability cue.

Once again, it is worthy of note that participants' search performance was unrelated to spatial and navigational abilities, as measured by the battery of individual differences tasks. This lack of a clear relationship may reflect the relatively sparse nature of the search environment, with fewer visual cues than are typically available in the large scale spatial tasks that are usually predicted by these measures (see Wolbers & Hegarty, 2010). Further related to this is the relative instability of the environment. In the present paradigm the search environment was extinguished between trials, which contrasts with the real world environments employed by Smith et al. (2010), and Jiang et al. (2014). This may cause initial difficulties for participants attempting to integrate the search environment across trials, when required to switch starting positions. Resolving the impermanence of the trial environment may instead be linked to spatial Working Memory (WM), which has been found to be a predictor of search efficiency in children (Smith et al., 2005).

GENERAL DISCUSSION

In the two experiments reported here, probabilistic cueing in large scale search was examined using a novel immersive VR methodology. Both experiments replicated research conducted by Smith et al. (2010; Experiments 2 and 3), with the methodology adapted for use in immersive VR. In each experiment reported here, participants were required to search for a hidden target, defined as the column (within an array of identical columns) that changed colour when it was activated. The location of the target was probabilistically determined, with 80% of targets being located in the cued hemispace, and 20% of targets appearing on the uncued hemispace. Participants' sensitivity to this cue was gauged with an array of dependent measures, which indicated whether participants biased their search to the cued region of space and, therefore, were less efficient at locating the target when it was in the uncued region.

Experiment 1 followed the design of Smith et al.'s (2010) Experiment 2, and broadly replicated their findings. A probabilistic cueing effect was observed in the behavioural measures, with participants demonstrating greater search efficiency (i.e. faster search time, shorter paths, and fewer inspections) when the target was located in the cued region. Additionally, over three probe questions, the majority of participants correctly identified the cued region. There was a discrepancy between the findings of this experiment and its progenitor, however, in first choice data: whereas Smith et al. (2010) found that participants were significantly more likely to begin their search in the cued region, this was not observed in the present experiment. First choice instead appeared to be driven by the proximity of a region to the starting position, as participants inspected a column in the region containing the closest column more often than chance. This likely results from the procedural differences between this experiment and those reported by Smith et al. (2010), as items to be inspected in the present experiment could be located within touching distance of the starting position, whereas in Smith et al. (2010), there was always a buffer zone containing no potential target objects between the starting position and the array.

Having established that probability cueing could be observed in a VR replication of a previous real-world paradigm, the second experiment examined whether participants were sensitive to a cue that was restricted to an allocentric reference frame. Since participants in Experiment 1 began each search trial from the same starting position, the cue was defined both in allocentric co-ordinates (i.e. it was more likely to appear in a particular half of the array) and egocentric co-ordinates (i.e. depending on counterbalancing, it was more likely to appear either to the right or the left of the starting position, when facing the array). The predictive properties of the starting position were, therefore, removed in Experiment 2 (a replication of Smith et al.'s [2010] Experiment 3) by introducing two starting positions at opposite ends of the mid-sagittal axis, which were used equally across the course of the experiment. The cued region remained fixed relative to the environment, although the changes in a participant's perspective meant that it no longer occupied a predictable egocentric region at start. Results from this experiment, like those from Smith et al.'s (2010) Experiment 3, revealed no probabilistic cueing effect – i.e. there was no evidence that targets in the cued region of space were located any more efficiently than targets in the uncued region. Furthermore, there was evidence to suggest that awareness of the probability manipulation was at chance level, across participants, and there was no evidence that awareness was related to the behavioural measures. Akin to the findings of Experiment 1, first choice behaviour appeared to be driven by the proximity of the search locations to the starting positions. This suggests that future experiments employing this sort of task should ensure there is sufficient distance between the starting positions and the array to more clearly isolate whether the initial inspection is driven by an awareness of the target's distribution in space.

These data represent the first demonstration of a large-scale probability cueing effect in immersive virtual reality. Not only do they replicate the previous findings of Smith et al. (2010), but they also extend them to a different search context, and provide an important proof-of-concept that behavioural effects observed in veridical environmental space can be reliably observed in a virtual equivalent. Interestingly, however, the data do not assist in the reconciliation of differential findings obtained by

Smith et al. (2010) and Jiang et al. (2014), with the latter demonstrating that probabilistic cueing can be observed in an allocentric spatial reference frame. Since the present findings are consistent across different manifestations of the basic Smith et al. (2010) paradigm, these broad differences in observing an allocentric basis to cueing might perhaps be explained by more fundamental procedural differences between the two tasks. Jiang et al.'s (2014) experiment was conducted outdoors on a university campus, where there was a great deal of visual information available to participants. In contrast, the experiments presented here and in Smith et al. (2010) were conducted in controlled laboratory spaces, with the only visual cue to environmental structure being the configuration of a stable search array. The VR environment was perceptually richer than the apparatus used by Smith et al. (2010), and general luminance levels were higher (to approximate daylight), but there was still an absence of extraneous (i.e. extra-array) visual cues to location and orientation, compared to those present in the naturalistic setting used by Jiang et al. (2014). It has previously been demonstrated that more impoverished visual environments can attenuate search efficiency (Ruddles & Lessels, 2006; 2009), and it would therefore make sense that participants in Jiang et al.'s (2014) study were able to develop a stronger allocentric representation of space, given a greater amount of available cues. This interpretation is supported by the results of Smith et al.'s (2010) Experiment 5, in which the two halves of the search array were differently coloured (i.e. red vs. green). Under those conditions, and with an alternating starting position, an 'allocentric' probability cueing effect was observed, presumably because the combination of allocentric information with an additional featural cue (i.e. a distinguishing colour) assisted sensitivity to search statistics (note that colour alone was not sufficient to cue participants in the same study). This evidence perhaps highlights the importance of salient landmarks when learning about a probabilistic spatial distribution in a fixed region of space.

Aside from the nature of the search environment, and cues available within it, it is also possible that the requirements of the search process itself might contribute to the presence or absence of particular behavioural effects (see: Gilchrist et al., 2001; Smith et al., 2008). In the experiments reported here, and in those reported by Smith et al. (2010), participants were required to physically explore the space, and interact with each potential search location in order to ascertain whether it was the target. This can be considered equivalent to a serial self-terminating (or ‘effortful’) search in the visual search domain, but where search itself is not visually guided by item-based characteristics (Duncan & Humphreys, 1989; Treisman & Gelade, 1980). However, in Jiang et al.’s (2014) study, participants were required to only locate the target and identify its colour, and could successfully complete the task from their starting position by visually scanning the environment. Physical exploration of an environment requires continual spatial updating in order to localise oneself in the context of the experimental environment (e.g. Gallistel, 1990). It is likely that this is more demanding than observing an array from a fixed perspective, and may therefore also contribute to the differences observed in probabilistic cueing across the studies. Indeed, this qualitative difference between the tasks is perhaps akin to the difference between a typical visual search task, in which the search array is commonly observed from a single perspective, and a large scale search task (as examined by Smith et al., 2008), with each task providing differing patterns of results.

It is important to note the difficulty in fully dissociating allocentric and egocentric contributions to spatial learning in large scale search. In Experiment 1, participants would be able to make use of both egocentric and allocentric spatial information at the trial’s start, however, once participants began to explore the space, the egocentric cue would be of limited use, as their viewpoint would move around the environment. This means that what was once to one side of them, would not remain so throughout the whole trial. To completely isolate an egocentric cue in search, the task would more closely resemble a traditional visual search task, with the array visible only from a single perspective. This would ensure that all viewpoint-centred spatial relations would remain the same, but is unachievable within the constraints of this task's design. Furthermore, in Experiment 2, those participants that appeared to search focus their search in the cued region may have been able to guide their initial search on the basis of two separate egocentric response strategies from each of the starting positions, i.e. that the target was more likely to appear on one side of the array relative to one starting position, and on the opposite side from the other starting position.

Alongside the environmental or task-related factors that might modulate the learning of statistical cues in search, we also aimed to identify potential individual differences that could underlie the presence or absence of a cueing effect. For example, a related study (Pellicano et al., 2011) found that children with autism were less likely to learn the same probabilistic cue than typically developing children, and that this was associated with the guidance of search behaviour (i.e. children with autism were, comparatively, less optimal and less systematic in their search paths). In the case of typical adults, as examined in the present study, it is generally apparent that some individuals learned about the cue, whereas other did not. As such, the absence of a general cueing effect in Experiment 2, may not necessarily reflect the absence of learning across the entire sample, but a noisier dataset. Identification of the factors that predict learning would, therefore, allow us to disentangle the relative contributions of paradigmatic differences to our understanding of cueing effects. We here focused on behavioural measures of small-scale spatial abilities that have previously been found to predict general navigational abilities (i.e. object rotation and viewpoint rotation), as well as self-report assays of sense of direction and handedness (for a more in-depth discussion of these factors, see: Hegarty et al., 2006; Wolbers & Hegarty, 2010). The results of our analyses were that none of these measures were associated with search performance in either of the experiments reported here. This is somewhat surprising in the case of Experiment 2, as one might expect that the spatial updating and spatial translation required to identify that the cued side of space was in a fixed region relative to the environment, are typically required in wayfinding behaviours. As such, one could therefore conclude that large-scale search, or the modulation of search behaviour on the basis of spatial statistics, are not functions that necessarily rely upon the same cognitive underpinnings as spatial navigation.

In contrast to exploring the individual predictors of cueing, analysis of the relationship between different indices of search behaviour might provide an alternative insight into inter-individual variability in performance (for a recent example, see: Munion et al., 2019). This process revealed significant correlations in Experiment 2, between behavioural measures of search efficiency (search latency, path length, and the difference between the number of columns inspected in the cued and uncued regions) and participants' first trial inspection being in the cued region throughout the experiment. This suggests that there were some participants that did learn about the probabilistic distribution of the target. The observation is further underpinned by the negative correlation between participants that tended to start their search with the closest column rather than the cued region. An interpretation of this negative association is that participants differed in terms of the rigidity, or systematicity, of their search patterns. So, whereas some participants modulated their search in response to the probabilistic cue, becoming more efficient over time, others systematically began their search with the closest target, irrespective of the cue, which negatively impacted upon efficiency. These individual differences in search strategy could be further explored by examining whether there is a link between measures of search efficiency and spatial working memory (WM). A link has already been identified in children, with a greater spatial WM span predicting more efficient search behaviour (Smith, Gilchrist, & Hood, 2005). Of further interest would be the dissociation between relational and locational spatial WM (Ackerman & Courtney, 2012; Blacker & Courtney, 2016). Relational spatial WM may be of particular interest to examine, as it was found to be a predictor of the ability to integrate the layout of landmarks on two distinct routes into a larger coherent mental representation of space (Blacker, Weisberg, Newcombe, & Courtney, 2017). This behaviour involved integrating spatial information across multiple different starting positions, so it may be that this similarity indicates shared underpinning cognitive processes.

It is, however, important to note that these potential differences in strategic approach may stem from participants not being able to reliably orient themselves at the start of each trial, and therefore that they may have been unable to distinguish the region in which the target was more likely to appear. A disoriented participant, if searching efficiently, would inspect the closest column to their starting position, and then proceed to inspect the remaining columns in a travelling salesman like approach (i.e. systematically work through the search array, minimising the amount of movement between inspections), which may be represented by participants initially inspecting columns in the closest side of the array to the starting position more often than column in the other side of the array. Furthermore, this disorientation may be shown by the effect of Trial Block on the Trial Latency measure in Experiment 2, as this might encapsulate participants' initial disorientation at the start of the experiment leading to longer initial trial latencies as they slowly orient, followed by shorter trial latencies that are facilitated by swifter reorientation at the start of each trial.

As we seek to devise paradigms and techniques for more valid, sensitive, and replicable laboratory assays of human search behaviour, it is encouraging that the experiments presented here provide support for the use of immersive VR in the experimental study of larger scale search behaviours. By employing immersive VR, we allowed participants full motility in exploring the VE, which affords some confidence that behaviour would not be affected by any potential artefacts derived from more artificial methods of exploration (Ruddles & Lessels, 2006; 2009). Additionally, the use of a wireless HMD removes a cue that could aid a participant's self-localisation (i.e. the HMD's cable). Furthermore, the use of immersive VR addresses some of the aforementioned broader issues that impact upon experimental studies of large scale spatial behaviour. For example, the immersive VE offers full control of the perceptual information available to the participant, thus eliminating some of the potential confounds present in previous studies, such as extraneous visual information (Jiang et al., 2014), whilst still affording specification of an environment that is not as quite as artificial or abstract as an array of lights presented on the floor of an laboratory (Smith et al., 2005; 2008; 2010; Pellicano et al., 2011). This level of control, therefore, facilitates further examination of the static and dynamic environmental cues that guide human search behaviour, in a manner that would not otherwise be possible.

The findings presented here reinforce the previous demonstration (Smith et al., 2010) that probabilistic cueing can be reliably observed in large-scale search when participants are able to combine allocentric and egocentric cues, but is not facilitated when egocentric cues have no predictive validity (i.e. the cue is solely specified within an allocentric spatial reference frame). It may be that different approaches to searching for the target (i.e. systematic search vs focusing on cued regions) underpin allocentric probabilistic cueing in visually impoverished scenes. Further research investigating individual differences in search strategy would, therefore, be a fruitful line of future research, and a more comprehensive battery of measures may be necessary to reveal the cognitive and perceptual underpinnings of variation.

REFERENCES

Ackerman, C. M., & Courtney, S. M. (2012). Spatial relations and spatial locations are dissociated within prefrontal and parietal cortex. *Journal of Neurophysiology*, *108*(9), 2419–2429. https://doi.org/10.1152/jn.01024.2011

Blacker, K. J., & Courtney, S. M. (2016). Distinct Neural Substrates for Maintaining Locations and Spatial Relations in Working Memory. *Frontiers in Human Neuroscience*, *10*(November), 1–17. https://doi.org/10.3389/fnhum.2016.00594

Blacker, K. J., Weisberg, S. M., Newcombe, N. S., & Courtney, S. M. (2017). Keeping track of where we are: Spatial working memory in navigation. *Visual Cognition*, *25*(7–8), 691–702. https://doi.org/10.1080/13506285.2017.1322652

Bostelmann, M., Lavenex, P., & Banta Lavenex, P. (2020). Children five-to-nine years old can use path integration to build a cognitive map without vision. *Cognitive Psychology*, *121*(January), 101307. https://doi.org/10.1016/j.cogpsych.2020.101307

Brady, T. F., & Chun, M. M. (2007). Spatial Constraints on Learning in Visual Search: Modeling Contextual Cuing. *Journal of Experimental Psychology: Human Perception and Performance*, *33*(4), 798–815. https://doi.org/10.1037/0096-1523.33.4.798

Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, *9*(2), 129–136. https://doi.org/10.1016/0040-5809(76)90040-X

Chua, K., & Chun, M. M. (2003). Implicit scene learning is viewpoint dependent. *Perception & Psychophysics*, *65*(1), 72–80. https://doi.org/10.3758/BF03194784

Chun, M. M., & Jiang, Y. V. (1998). Contextual cueing: implicit learning and memory of visual context guides spatial attention. *Cognitive Psychology*, *36*(1), 28–71. https://doi.org/S0010-0285(98)90681-8 [pii] 10.1006/cogp.1998.0681 ET - 1998/07/29

De Lillo, C., & James, F. C. (2012). Spatial working memory for clustered and linear configurations of sites in a virtual reality foraging task. *Cognitive Processing*, *13*(1 SUPPL). https://doi.org/10.1007/s10339-012-0448-x

De Lillo, C., Kirby, M., & James, F. C. (2014). Spatial working memory in immersive virtual reality foraging: Path organization, traveling distance and search efficiency in humans (Homo sapiens). *American Journal of Primatology*, *76*(5), 436–446. https://doi.org/10.1002/ajp.22195

De Lillo, C., Kirby, M., & James, F. C. (2014). Spatial working memory in immersive virtual reality foraging: Path organization, traveling distance and search efficiency in humans (Homo sapiens). *American Journal of Primatology*, *76*(5), 436–446. https://doi.org/10.1002/ajp.22195

De Lillo, C., Kirby, M., & James, F. C. (2014). Spatial working memory in immersive virtual reality foraging: Path organization, traveling distance and search efficiency in humans (Homo sapiens). *American Journal of Primatology*, *76*(5), 436–446. https://doi.org/10.1002/ajp.22195

Dienes, Z. (2014). Using Bayes to get the most out of non-significant results. *Frontiers in Psychology*, *5*(July), 1–17. https://doi.org/10.3389/fpsyg.2014.00781

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458. https://doi.org/10.1037/0033-295X.96.3.433

Gallistel, C. R. (1990). *The organization of learning.* (1st ed.). Cambridge, MA: The MIT Press. Retrieved from http://psycnet.apa.org/record/1990-98569-000

Geng, J. J., & Behrmann, M. (2002). Probability cuing of target location facilitates visual search implicitly in normal participants and patients with hemispatial neglect. *Psychological Science*, *13*(6), 520–525. https://doi.org/10.1111/1467-9280.00491

Geng, J. J., & Behrmann, M. (2005). Spatial probability as an attentional cue in visual search. *Perception & Psychophysics*, *67*(7), 1252–1268. https://doi.org/10.3758/BF03193557

Gilchrist, I. D., North, A., & Hood, B. M. (2001). Is visual search really like foraging? *Perception*, *30*(12), 1459–1464. https://doi.org/10.1068/p3249

Hegarty, M., Montello, D. R., Richardson, A. E., Ishikawa, T., & Lovelace, K. (2006). Spatial abilities at different scales: Individual differences in aptitude-test performance and spatial-layout learning. *Intelligence*, *34*(2), 151–176. https://doi.org/10.1016/j.intell.2005.09.005

Hegarty, M., Richardson, A. E., Montello, D. R., Lovelace, K., & Subbiah, I. (2002). Development of a self-report measure of environmental spatial ability. *Intelligence*, *30*(5), 425–447. https://doi.org/10.1016/S0160-2896(02)00116-2

Jeffreys, H. (1998). *The theory of probability*. OUP Oxford.

Jiang, Y. V., & Swallow, K. M. (2013). Spatial reference frame of incidentally learned attention. *Cognition*, *126*(3), 378–390. https://doi.org/10.1016/j.cognition.2012.10.011

Jiang, Y. V., & Won, B. Y. (2015). Spatial scale, rather than nature of task or locomotion, modulates the spatial reference frame of attention. *Journal of Experimental Psychology: Human Perception and Performance*, *41*(3), 866–878. https://doi.org/10.1037/xhp0000056

Jiang, Y. V., Swallow, K. M., & Capistrano, C. G. (2013). Visual search and location probability learning from variable perspectives. *Journal of Vision*, *13*(6), 1–13. https://doi.org/10.1167/13.6.13

Jiang, Y. V., Won, B. Y., Swallow, K. M., & Mussack, D. M. (2014). Spatial reference frame of attention in a large outdoor environment. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(4), 1346–1357. https://doi.org/10.1037/a0036779

Kelly, R. L. (1995). *The foraging spectrum: Diversity in hunter-gatherer lifeways*. Smithsonian Inst Press.

Klein, R. M., & MacInnes, W. J. (1999). Inhibition of return is a foraging facilitator in visual search. *Psychological Science*, *10*(4), 346–352. https://doi.org/10.1111/1467-9280.00166

Kozhevnikov, M., & Hegarty, M. (2001). A dissociation between object manipulation spatial ability and spatial orientation ability. *Memory and Cognition*, *29*(5), 745–756. https://doi.org/10.3758/BF03200477

Kozhevnikov, M., Motes, M. A., Rasch, B., & Blajenkova, O. (2006). Perspective-taking vs. mental rotation transformations and how they predict spatial navigation performance. *Applied Cognitive Psychology*, *20*(3), 397–417. https://doi.org/10.1002/acp.1192

Li, C., Aivar, M. P., Kit, D. M., Tong, M. H., & Hayhoe, M. M. (2016). Memory and visual search in naturalistic 2D and 3D environments, *16*, 1–20. https://doi.org/10.1167/16.8.9.doi

Li, C.-L., Aivar, M. P., Tong, M. H., & Hayhoe, M. M. (2018). Memory shapes visual search strategies in large-scale environments. *Scientific Reports*, *8*(1), 1–11. https://doi.org/10.1038/s41598-018-22731-w

Maya, C., Rosetti, M. F., Pacheco-Cobos, L., & Hudson, R. (2019). Human Foragers: Searchers by Nature and Experience. *Evolutionary Psychology*, *17*(2), 1–9. https://doi.org/10.1177/1474704919839729

Munion, A. K., Stefanucci, J. K., Rovira, E., Squire, P., & Hendricks, M. (2019). Gender differences in spatial navigation: Characterizing wayfinding behaviors. *Psychonomic Bulletin and Review*, *26*(6), 1933–1940. https://doi.org/10.3758/s13423-019-01659-w

Newcombe, N. S. (2018). Individual variation in human navigation. *Current Biology*, *28*(17), R1004–R1008. https://doi.org/10.1016/j.cub.2018.04.053

Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia*, *9*(1), 97–113. https://doi.org/10.1016/0028-3932(71)90067-4

Pashler, H., & Wagenmakers, E.-J. (2012). Editors' Introduction to the Special Section on Replicability in Psychological Science: A Crisis of Confidence? *Perspectives on Psychological Science*, *7*(6), 528–530. https://doi.org/10.1177/1745691612465253

Pellicano, E., Smith, A. D., Cristino, F., Hood, B. M., Briscoe, J., & Gilchrist, I. D. (2011). Children with autism are neither systematic nor optimal foragers. *Proceedings of the National Academy of Sciences*, *108*(1), 421–426. https://doi.org/10.1073/pnas.1014076108

Peters, M., Laeng, B., Latham, K., Jackson, M., Zaiyouna, R., & Richardson, C. (1995). A redrawn vandenberg and kuse mental rotations test - different versions and factors that affect performance. *Brain and Cognition*. https://doi.org/10.1006/brcg.1995.1032

Rosetti, M., Rodríguez, A., Pacheco-Cobos, L., & Hudson, R. (2016). An experimental task to explore the effects of age and sex on social foraging behavior. *Evolutionary Behavioral Sciences*, *10*(3), 168–178. https://doi.org/10.1037/ebs0000053

Ruddle, R. A., & Lessels, S. (2009). The benefits of using a walking interface to navigate virtual environments. *ACM Transactions on Computer-Human Interaction*, *16*(1), 1–18. https://doi.org/10.1145/1502800.1502805

Schachter, S. C. (2000). The quantification and definition of handedness: Implications for handedness research. In *Side bias: A neuropsychological perspective* (pp. 155-174). Springer, Dordrecht.

Schinazi, V. R., Nardi, D., Newcombe, N. S., Shipley, T. F., & Epstein, R. A. (2013). Hippocampal size predicts rapid learning of a cognitive map in humans. *Hippocampus*, *23*(6), 515–528. https://doi.org/10.1002/hipo.22111

Smith, A. D., Gilchrist, I. D., & Hood, B. M. (2005). Children's search behaviour in large-scale space: Developmental components of exploration. *Perception*, *34*(10), 1221–1229. https://doi.org/10.1068/p5270

Smith, A. D., Gilchrist, I. D., Hood, B. M., Tassabehji, M., & Karmiloff-Smith, A. (2009). Inefficient search of large-scale space in Williams syndrome: Further insights on the role of LIMK1 deletion in deficits of spatial cognition. *Perception*, *38*(5), 694–701. https://doi.org/10.1068/p6050

Smith, A. D., Hood, B. M., & Gilchrist, I. D. (2008). Visual search and foraging compared in a large-scale search task. *Cognitive Processing*, *9*(2), 121–126. https://doi.org/10.1007/s10339-007-0200-0

Smith, A. D., Hood, B. M., & Gilchrist, I. D. (2010). Probabilistic cuing in large-scale environmental search. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *36*(3), 605–618. https://doi.org/10.1037/a0018280

Sosa, Y., Teder-Sälejärvi, W. A., & McCourt, M. E. (2010). Biases of spatial attention in vision and audition. *Brain and Cognition*, *73*(3), 229–235. https://doi.org/10.1016/j.bandc.2010.05.007

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136. https://doi.org/10.1016/0010-0285(80)90005-5

Vadillo, M. A., Linssen, D., Orgaz, C., Parsons, S., & Shanks, D. R. (2019). Unconscious or Underpowered? Probabilistic Cuing of Visual Attention. *Journal of Experimental Psychology: General*. https://doi.org/10.1037/xge0000632

Vandenberg, S. G., & Kuse, A. R. (1978). Mental rotations, a group test of three-dimensional spatial visualization. *Perceptual and Motor Skills*, *47*(2), 599–604. https://doi.org/10.2466/pms.1978.47.2.599

Walthew, C., & Gilchrist, I. D. (2006). Target location probability effects in visual search: An effect of sequential dependencies. *Journal of Experimental Psychology: Human Perception and Performance*, *32*(5), 1294–1301. https://doi.org/10.1037/0096-1523.32.5.1294

Wolbers, T., & Hegarty, M. (2010). What determines our navigational abilities? *Trends in Cognitive Sciences*, *14*(3), 138–146. https://doi.org/10.1016/j.tics.2010.01.001

Table 1. Correlation matrix and p values for variables in Experiment 1. FCCue = Percentage trials with first choice in cued region, FCClo = Percentage trials starting with first choice of closest column, MRT = Mental Rotation Task accuracy, PTE = Perspective taking task error, SBSOD = Santa Barbara Sense of Direction Scale, LQ = Amended Edinburgh Handedness Inventory Laterality Quotient, PA = Probe question level of awareness, LatDiff = Difference between latency to find target on cued and uncued trials, InspDiff = Difference between number of inspections on cued and uncued trials, PathDiff = Difference between path length on cued and uncued trials.

Table 2. Correlation matrix and p values for variables in Experiment 2. FCCue = Percentage trials with first choice in cued region, FCClo = Percentage trials starting with first choice of closest column, MRT = Mental Rotation Task accuracy, PTE = Perspective taking task error, SBSOD = Santa Barbara Sense of Direction Scale, LQ = Amended Edinburgh Handedness Inventory Laterality Quotient, PA = Probe question awareness, LatDiff = Difference between latency to find target on cued and uncued trials, InspDiff = Difference between number of inspections on cued and uncued trials, PathDiff = Difference between path length on cued and uncued trials.

Figure 1. A schematic diagram of the virtual environment. The two hemispaces of potential column locations are indicated by the smaller white and grey circles. The two larger white and black circles represent starting positions. In Experiment 1, only the white starting position was used, whereas in Experiment 2, the identity of the starting position for each trial was randomised under constraints.

Figure 2. Screenshots taken from the experimental task showing (A) a top down view of the experimental environment, (B) the experimental trial environment, and (C) the practice trial

environment. Image D shows the VR equipment employed in this study, as well as the space in which the experiments were conducted.

Figure 3. Data visualisation for Experiment 1. Each violin plot shows the distribution of the condition along its flank, and each participant's mean score along its central axis. The crossbars show the mean value per condition, and are bounded by standard error. In plot D, the chance value of 50% is indicated by the dashed horizontal line.

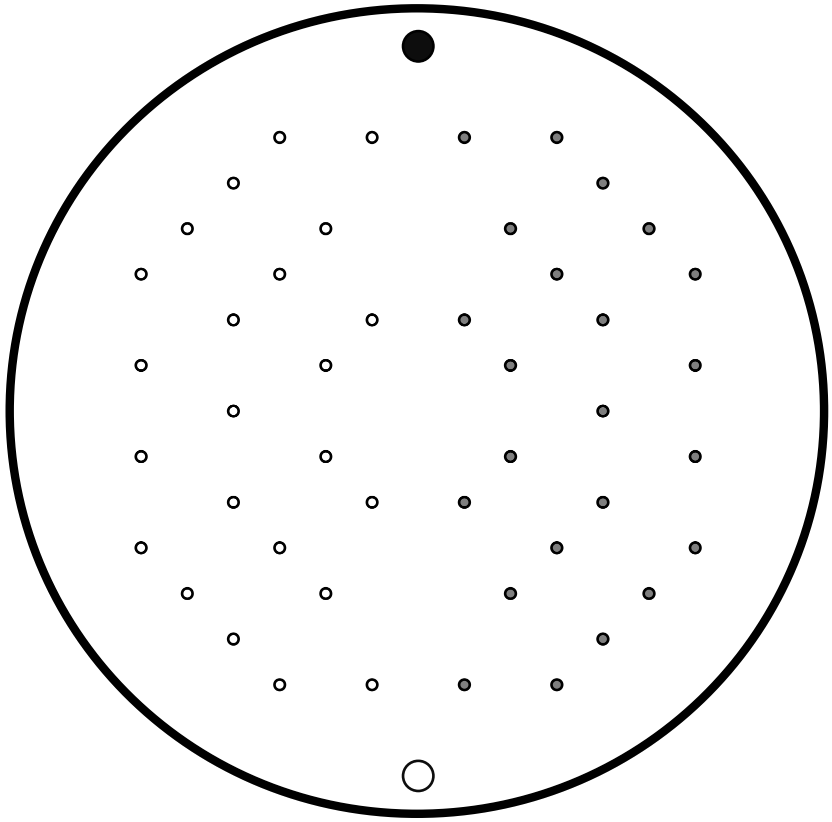
Figure 4. Data visualisation for Experiment 2. Each violin plot shows the distribution of the condition along its flank, and each participant's mean score along its central axis. The crossbars show the mean value per condition, and are bounded by standard error. In plot D, the chance value of 50% is indicated by the dashed horizontal line.

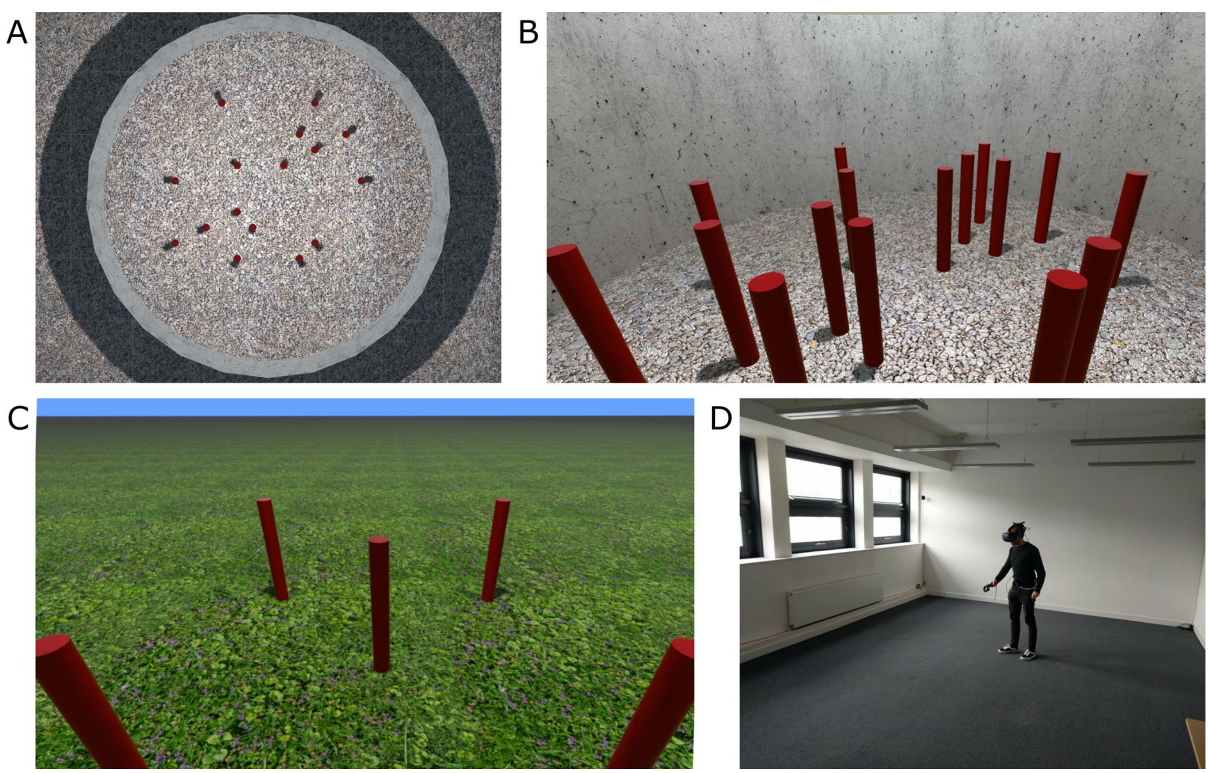
	FCCue	FCClo	Revisits	MRT	PTE	SBSOD	LQ	PA	LatDiff	InspDiff	PathDiff
FCCue	1										
FCClo	-0.19	1									
Revisits	-0.09	-0.08	1								
MRT	-0.16	0.15	-0.4	1							
PTE	0.31	0.05	0.24	-0.04	1						
SBSOD	0.15	-0.23	-0.16	-0.1	0.03	1					
LQ	-0.08	-0.47*	-0.02	-0.08	-0.1	-0.51*	1				
PA	-0.11	0.1	-0.39	0.2	-0	0.09	-0.1	1			
LatDiff	0.29	-0.14	-0.19	-0.33	-0.3	0.15	-0.2	0	1		
InspDiff	0.22	-0.2	-0.28	-0.28	-0.3	0.14	-0.1	0	0.92****	1	
PathDiff	0.22	-0.22	-0.32	-0.2	-0.3	0.15	-0.1	-0	0.92****	0.99****	1

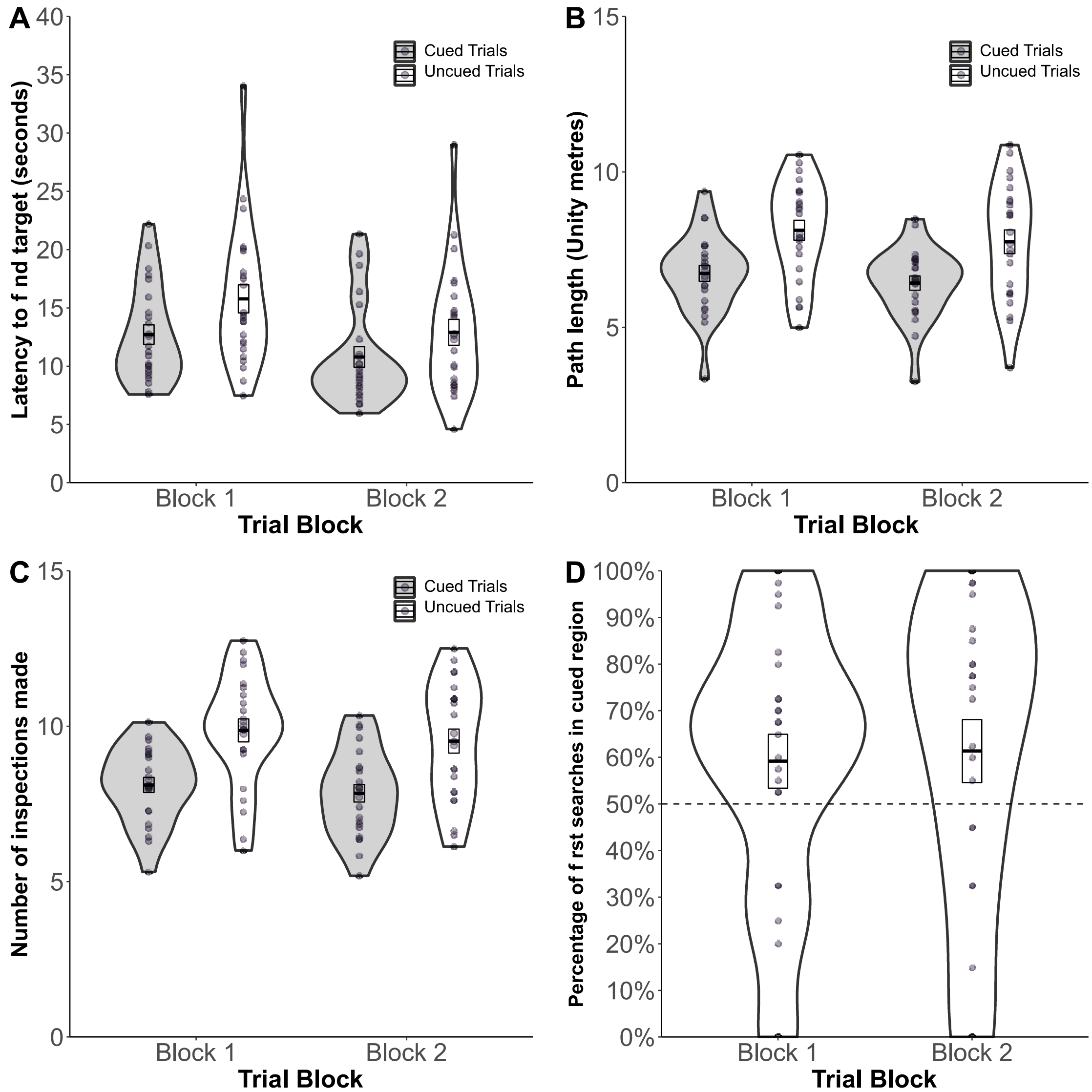
p < .0001 '****'; p < .001 '***', p < .01 '**', p < .05 '*'

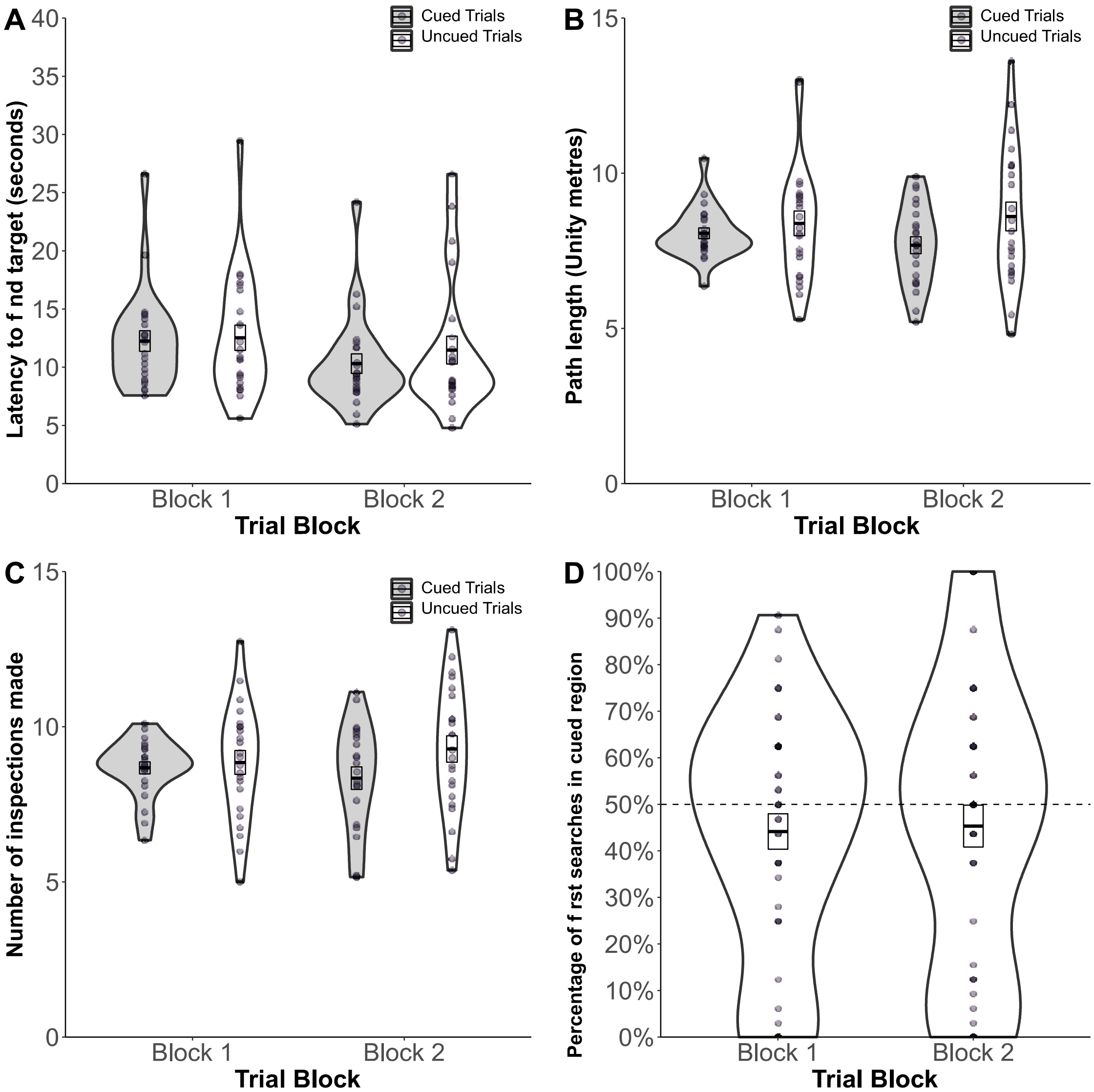
	FCCue	FCClo	Revisits	MRT	PTE	SBSOD	LQ	PA	LatDiff	InspDiff	PathDiff
FCCue	1										
FCClo	-0.45*	1									
Revisits	0.22	-0.48*	1								
MRT	-0.15	0.11	-0.07	1							
PTE	-0.12	0.08	-0.16	-0.63**	1						
SBSOD	-0.04	-0.37	0	-0.31	0.13	1					
LQ	0.06	-0.18	-0.01	-0.16	0	0.11	1				
PA	-0.36	0.37	-0.04	0.01	0.36	-0.29	-0.2	1			
LatDiff	0.46*	-0.02	0.17	-0.15	0	-0.09	0.12	0.2	1		
InspDiff	0.49*	-0.02	0.14	-0.17	-0.1	-0.14	0.19	0.1	0.94****	1	
PathDiff	0.49*	-0.08	0.19	-0.14	-0.1	-0.12	0.28	0.1	0.93****	0.96****	1

p < .0001 '****'; p < .001 '***', p < .01 '**', p < .05 '*'




A
B
C
D


A
Latency to f nd target (seconds)
Cued Trials
Uncued Trials
Block 1
Block 2
Trial Block
B
Path length (Unity metres)
Cued Trials
Uncued Trials
Block 1
Block 2
Trial Block
C
Number of inspections made
Cued Trials
Uncued Trials
Block 1
Block 2
Trial Block
D
Percentage of f rst searches in cued region
Block 1
Block 2
Trial Block


A
Cued Trials
Uncued Trials
Latency to f nd target (seconds)
0
5
10
15
20
25
30
35
40
Block 1
Block 2
Trial Block
B
Path length (Unity metres)
0
5
10
15
C
Number of inspections made
D
Percentage of f rst searches in cued region
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%